

Virtual Biomedical and STEM/STEAM Education

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PATTERN RECOGNITION IN BIOMEDICAL ENGINEERING

FEATURE EXTRACTION AND SELECTION







Introduction to Feature Engineering

- Definition: Feature engineering involves creating and selecting the most relevant features for predictive models.
- Role in Biomedical Engineering: Critical for interpreting complex data like images, signals, and genetic information.
- Types of Biomedical Data: Imaging, Signals, Genomics, etc.















Feature Extraction

- Definition: Process of transforming raw data into informative features.
- Techniques:
 - Signal Processing for biomedical signals (e.g., wavelet transforms for ECG)
 - Texture Analysis for Images (e.g., GLCM for MRI)
 - Dimensionality Reduction (e.g., PCA for high-dimensional data)
- Examples: Specific features extracted from ECG, MRI, and genetic data.







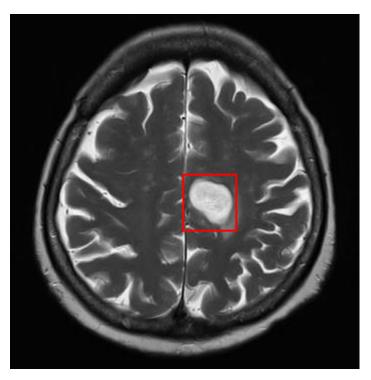








• Structural Features: Shape, size, and location information.



- ➤ Number of pixels (area)
- ➤ Bounding box
- ➤ Center of mass (centroid)
- ➤ Circularity
- >...















Statistical Features: Mean, variance, skewness, etc.

N	1	2	3
White blood cells [no/µl]	5600	9000	4800
Red blood cells [no/µl]	4.8x106	4.1x106	4.6x106
Platelet count [no/µl]	142,000	148,000	151,000
Hemoglobin [g/dl]	12.2	13.4	12.5
Glucose [mg/dl]	71	74	72







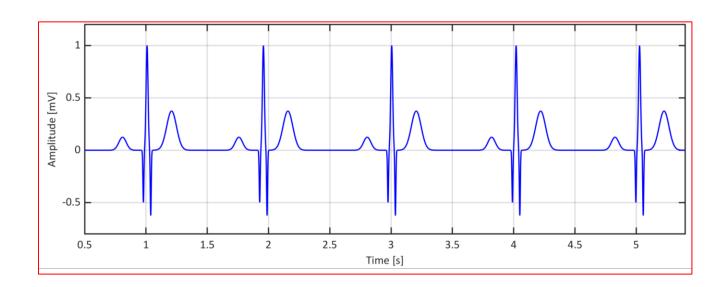








• Temporal Features: Patterns over time (e.g., ECG signals).



HRV = 0.05 s







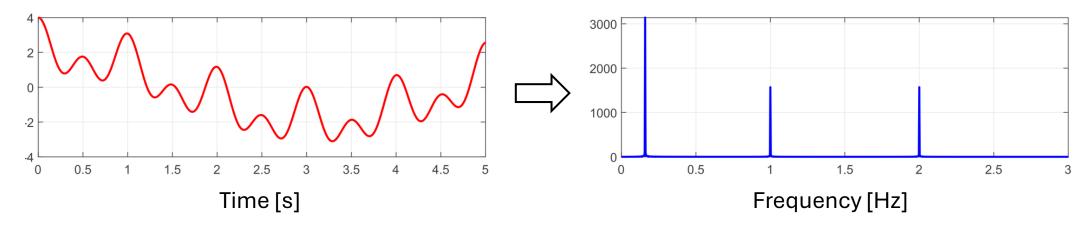








Frequency-Domain Features: Derived from signal transformations



$$X(\omega) = \sum_{n=-\infty}^{n=+\infty} x(n)e^{-j\omega n}, \omega \in (-\pi, \pi)$$

Source: Original work by the author.















Feature importance analysis



Analysis of Variance (ANOVA)

$$F = \frac{Between - group \ variance}{Within - grop \ variance} = \frac{\sum_{k=1}^{K} n_k (\overline{x}_k - \overline{x})^2 / (K - 1)}{\sum_{k=1}^{K} \sum_{i=1}^{n_k} \left(x_{i,k} - \overline{x}_k \right)^2 / (N - K)},$$

Where:

- K: number of groups (categories of the target variable)
- N: total number of observations
- n_k: number of observations in the k-th group
- \overline{x} : overall mean
- \overline{x}_k : mean of the k-th group















Minimum Redundancy Maximum Relevance (MRMR)

- Relevance : $I(X_i; Y) = \sum_{x_i \in X_i} \sum_{y \in Y} P(x_i, y) \log \frac{P(x_i, y)}{P(x_i)P(y)}$
- Redundancy: $I(X_i; X_j) = \sum_{x_i \in X_i} \sum_{x_j \in X_j} P(x_i, x_j) \log \frac{P(x_i, x_j)}{P(x_i)P(x_j)}$
- MRMR Criterion:

$$MRMR = \max\left(\frac{1}{|S|}\sum_{X_i \in S} I(X_i; Y) - \frac{1}{|S|^2}\sum_{X_i, X_j \in S} I(X_i; X_j)\right)$$















Feature selection



Wrapper Methods

Forward Feature Selection

- 1. Rank features based on their importance
- 2. Train the model on small number of features
- Iteratively add features to a model until the desired performance is reached















Wrapper Methods

Backward Feature Elimination

- 1. Train model on all features
- 2. Rank features based on their importance
- 3. Eliminate the least important features and repeat until the desired numer of features is reached







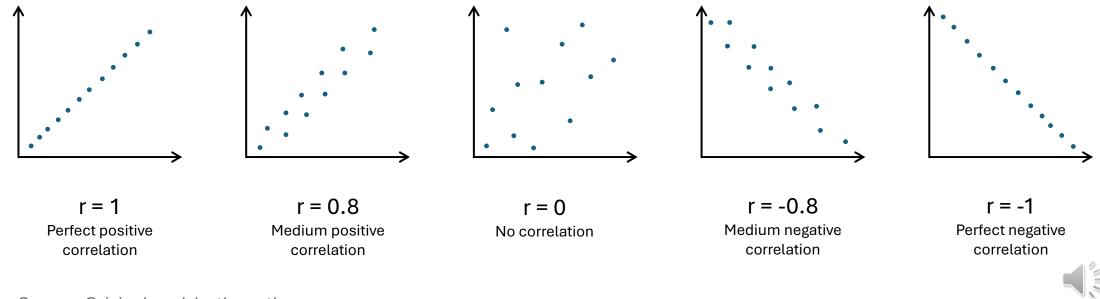






Filter Methods

Correlation analysis











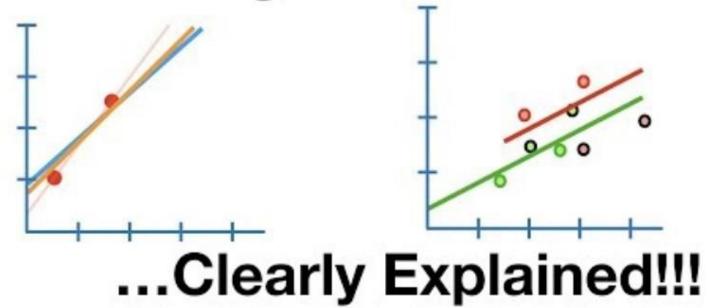






Embedded Methods

Lasso Regression....



Source: https://www.youtube.com/watch?v=NGf0voTMlcs







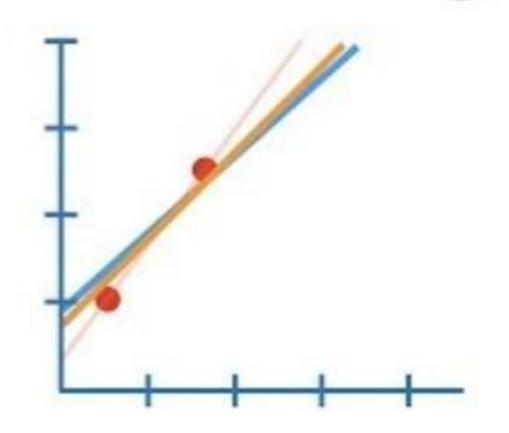


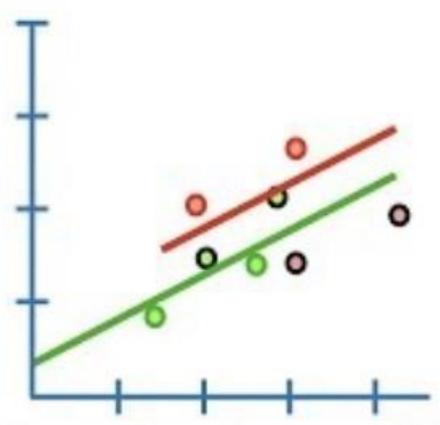






Lasso Regression....





Challenges and Considerations in Biomedical Feature Engineering



Data Variability

- Biological differences
- Calibration
- Equipment
- Human error

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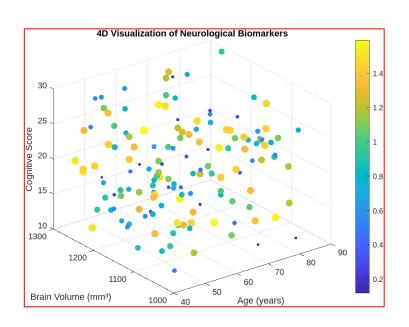


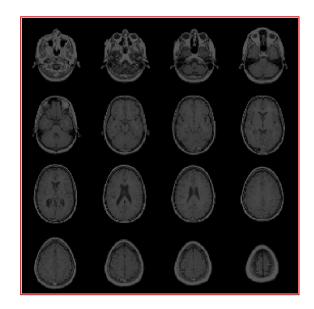


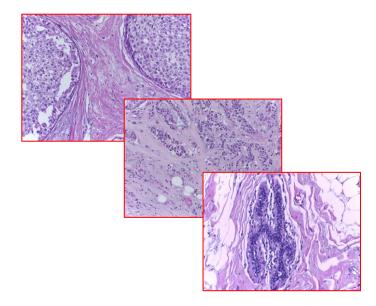


High Dimensionality & Small Sample Sizes

Common in biomedical data, leading to overfitting risks.









Source: Original work by the author; Mathworks Inc. MRI dataset; BACH: Breast Cancer Histology images.







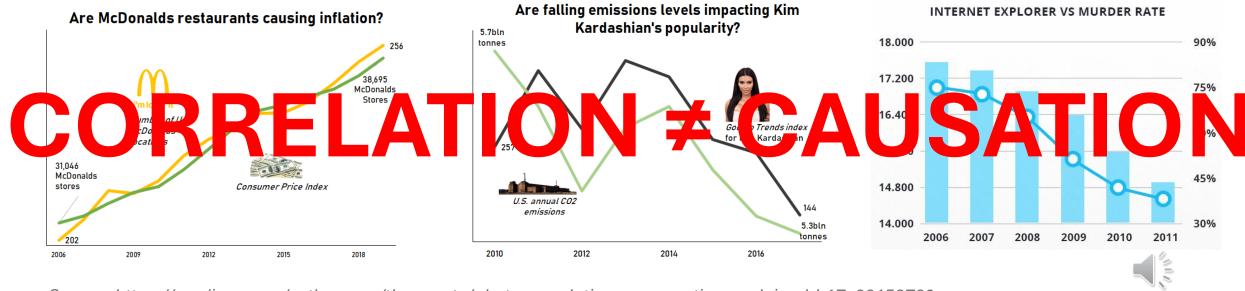






Interpretability

• Ensuring features are meaningful and interpretable for clinical use.



Source: https://medium.com/pythoneers/the-great-debate-correlation-vs-causation-explained-b17e98158760













Case study



ECG Feature Extraction for Arrhythmia Detection

Objective: Detect arrhythmias using ECG signal features.

Steps:

- 1. Preprocessing Remove noise and artifacts
- 2. Feature extraction
 - RR Interval (time between consecutive R-wave peaks): Indicates heart rhythm.
 - P-Wave Duration: Duration of atrial depolarization.
 - Frequency Analysis: Apply Fourier transform to detect frequency bands of interest.
- 3. Feature selection
 - Use filter methods to select features that correlate with arrhythmias.
 - Implement wrapper methods to test feature effectiveness in machine learning models.
- 4. Classification















Conclusion

- Summary: Reviewed feature types, extraction methods, and selection techniques.
- Further Reading:
 - Biomedical Data Science resources
 - Advanced texts on feature engineering in biomedical contexts















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